



Figure: Association of the test strategy with the ML Life Cycle

ML Test Strategy

The objective of testing is to provide sufficient information on the quality of the system under test, a DNN-based object detection function, for example. The ML Test Strategy of KI Absicherung provides a non-exclusive set of recommendations of methods to be used for testing DNN-based object detection functions. The ML Test Strategy is specified in relation to the ML Life Cycle (s. figure) and also addresses verification activities for the datasets. The activities are described below. For most method classes several concrete methods were developed in the project.

Dataset Verification & Coverage Analysis

Objectives:

- Verification of the training datasets, the development datasets and the test datasets (e.g. w.r.t. ODD coverage, balance/fairness, diversity, coverage of corner cases, coverage of decision boundaries or out-of-distribution samples)
- Provide qualitative & quantitative evidence for the quality and coverage of the datasets

Methods:

- Verify independence of test & training sets
- Analyze data collection gaps
- Analyze data fidelity
- Verify ODD coverage of test sets
- Verify that safety relevant cases are substantively represented in test sets
- Analyze statistical relevance of test sets

Data Pool Verification

Objectives:

- Verify label quality of the datasets

Methods:

- Label quality analysis

Neural Network Component Test

Objectives:

- Independently verify the trained NN model
- Provide qualitative and quantitative (esp. stochastic) evidence for the quality of the NN model

Methods:

- Define a strategy that allows for iterated testing
- Verify that the results on safety relevant cases are sufficiently reflected in KPIs
- Perform test-set-based statistical testing
- Perform NN model analysis/review
- Perform tests based on corner cases and expert knowledge
- Perform search-based testing
- Perform coverage-guided testing
- Perform robustness analysis
- Analyze resource limitations

ML Integration & Qualification Test

If two or more components containing NN models are integrated, one needs to consider whether they are stochastically independent or not. If they are, normal integration testing is applicable. Otherwise, specific methods are required that reflect the ML nature of the unit under test (s. above). For example, a threat to stochastic independence would be to use the same datasets for testing both components.

Identifier	Name	AP	Developer	EWS
MECH-018870	Adversarial Augmentation of Point Clouds for Domain Generalization	AP3.3	BMW	-
MECH-018870	Aversarial Robustness Toolbox (ART), Adversarial Attacks Assessment	AP3.3	BMW	-
MECH-156340	Heatmap based attention consistency validation	AP3.4	BMW, fortiss	-
MECH-936804	Formal verification of robustness properties	AP3.4	BMW	-
MECH-418874	Photometric Robustness Estimation	AP3.4	EPS	-
MECH-133124	Robustness Testing Framework	AP3.5	Merantix	EW52
MECH-376159	Distorted Images Assessment	AP3.5	Opel	EW52
MECH-116617	Visual analytics	AP3.6	Fraunhofer IAIS	EW53
TSTM-0001	Coverage guided fuzzing testing framework	AP4.4	BMW	EW52
TSTM-0004	Combinatorial testing	AP4.4	Bosch	EW58
TSTM-0005	Search based testing for computer vision	AP4.4	Bosch	EW54
TSTM-0007	Neuron Coverage guided fuzzing testing framework	AP4.4	BMW, fortiss	-
TSTM-0011 "Valerie"	Methodology to identify influencing parameters	AP4.4	Intel	EW54
TSTM-0012	Robustness Testing based on augmented (natural) corruption	AP4.4	Neurocat	EW52

Table: Example methods linked to the test strategy



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